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"Measuring unfairness"

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Measuring unfairness

An application to education and health in Argentina [1]

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Abstract

This paper presents a theoretical framework to measure unfairness in the distribution of an outcome. The framework is applied to goods and services for which societies have a concern about their distributions; chiefly, basic education and health care. The determinants of the consumption of, say, education are divided into socially acceptable and unacceptable sources of differences in individual education levels. To detect an unfair situation, comparisons are restricted to those individuals who share the same value of the vector of acceptable factors. The relevant variable to compare is the expectation of education consumption conditional on the vector of unacceptable variables. Unfairness in education is related to inequality in the distribution of those conditional expectations across individuals. Empirical results are obtained using data for the Greater Buenos Aires area and other Argentine cities. In particular, unfairness indices pertaining to secondary school, college, and visits to a doctor are calculated using non-parametric and parametric techniques.

1. *Introduction*

Most of the studies in welfare economics aimed at measuring the fairness of social arrangements are focused on the distribution of individual utility, usually estimated by the distribution of income or total consumption. According to this utilitarian approach, the measurement of inequality in the consumption of a particular good is not relevant: goods are just arguments of the individual's utility, and only the latter should be of concern in a non-paternalistic society. However, in the real world, politicians, policy-makers, and people in general seem to care about the distribution of particular goods and services. Two prominent examples are basic education and health.[3] Public programs aimed at attaining equality in the

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[1] I would like to thank Angus Deaton, Igal Hendel, Mariana Marchionni, Walter Sosa Escudero and seminar participants at Universidad Nacional de La Plata, the 10th Annual Inter-American Seminar on Economics, NBER (Santiago) and the 54th Congress of the International Institute of Public Finance (Córdoba) for helpful comments and suggestions. I also want to think Laura Ripani for providing efficient research assistance and Cristina Flood, Marcela Harriague and Diego Petrecolla for helping me to gather the data. Of course, the usual disclaimer applies.

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[3] Regarding education, and just to mention one of many examples, the new Argentine Constitution establishes that it is the authority of the National Congress "to make laws regarding the organization of education

consumption of education and health seem to be more popular than programs whose main goal is the improvement of the current distribution of income. Rightists and leftists often agree upon the social desirability of a more equal distribution of those basic services, but tend to disagree when discussing income distribution.

There are normative arguments behind this concern. It has long been sustained that in order to assess the fairness of a social arrangement, the emphasis should be placed on the distribution of the opportunities to attain certain outcomes, rather than on the distribution of those outcomes. Disparities in outcomes might be perfectly consistent with equal opportunities. Social scientists have championed different interpretations of the concept of equality of opportunity.[4] These ideas share the notion that the equalization of the "starting conditions" from where people shape their lives should be of primary social concern. It is relatively non-controversial to consider an individual's educational level and health status important factors in determining his set of opportunities. Therefore, the fairness in the distribution of at least certain basic levels of education and health consumption should be of social concern.

Despite the practical and theoretical interest on the fairness in the distribution of education and health, little work has been done in developing a systematic framework to measure the degree of unfairness in those services. This paper takes a step in that direction by presenting an approach based on the idea of *unacceptable inequality*. Variables that determine individual consumption of, say, education are divided into *acceptable* and *unacceptable* sources of differences in education consumption. Only the inequality in education consumption that is due to differences in *unacceptable* variables is considered unfair. A particular problem is posed by the fact that variables are typically stochastic. If the intrinsic random component in the consumption of education is considered an *acceptable* source of inequality, then the *expectation* of education consumption conditional on the unacceptable variables should be the object of comparison among individuals.

The rest of the paper is organized as follows. In section 2 the basic framework is presented and some empirical implementation problems are discussed. In section 3 unfairness indices pertaining to education and health services in the Greater Buenos Aires area and other Argentine cities are calculated using non-parametric and parametric techniques. Finally, section 4 concludes.

2. *The framework*

A concern for the distribution of a given outcome can take two different forms depending on whether the causes of that outcome are given relevance in assessing the fairness in the

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which...ensure...the equality of opportunity and guarantee the principles of equity and free of charge provision of public education" (Constitución Argentina (1994), article 75, clause 19). In the health literature, it has long been acknowledged that people have a concern about equity in the distribution of health services. For many, equity is arguably the prime consideration (see *Le Grand* (1991)).

[4] See *Sen* (1992) who surveys the concepts of equality of primary goods (Rawls), equality of resources (Dworkin) and equality of capabilities (Sen).

outcome distribution. If only the outcomes and not their causes are considered relevant, a situation will be regarded as unfair whenever two individual outcomes differ, regardless of the causes of that difference.[5] As argued above, people tend to go beyond outcomes and have a concern about their determinants. An unequal distribution of an outcome may be labeled as fair if the process by which it is generated is considered fair.

But how should we assess the fairness of that process? The dominant approach in the field of economics is that of equality of choice sets.[6] Factors that determine an outcome are divided into those that are given to an individual, and those that she freely chooses. For a difference in outcomes to be considered unfair, it should be the result of differences in factors in the former group. The problem of this approach is that in most practical situations the distinction between *constraint* and *choice* is not clear. One can argue that most, and probably all factors that determine an outcome are in a sense beyond individual control: a person does not choose her preferences, her talent, her cost of exerting effort, or her rationality. Therefore, all of these variables should be included in the constraint set. But as soon as we do so, the notion of choice becomes trivial.

I prefer to avoid this philosophical discussion and focus on the *acceptability* of the sources of differences. Inequality in a given outcome across individuals can be thought of as the result of individual differences in its explanatory variables. People tend to consider inequality as fair or unfair, depending on the sources of that inequality. Differences in the college attendance decision among youngsters may be considered fair if they are the result of differences in talent, effort or luck. But the same attendance differences might be labeled as unfair if their sources are differences in parental income, race or gender.

Notice that talent, the cost of exerting effort, luck, parental income, race and gender are all beyond individual control. However, for some reason, people tend to consider differences in some of them *acceptable* sources of inequality in college attendance, and differences in some others *unacceptable* sources. Of course different people have different views about how to partition the set of explanatory variables. Some people, for instance, would regard ability as an acceptable source of differences in outcomes; while for some others that would be unacceptable.[7] Rightists surely have a larger set of *acceptable* variables than leftists do. Societies also differ in the sources of inequities that, on average, are prepared to accept.[8]

From the above discussion we conclude that the partition of the set of explanatory variables into acceptable or unacceptable sources of outcome differences depends on value

[5] A typical income distribution analysis fits into this framework. The factors that determine incomes are not scrutinized. All that matters are the actual income values, and not the process by which they are generated.

[6] See *Archibald and Donaldson* (1979), *Le Grand* (1984 and 1991), *Gravel* (1994), *Thomson* (1994) and *Roemer* (1997).

[7] See *Denison* (1970) for a discussion on the acceptability of ability in determining college admissions.

[8] "Americans commonly perceive differences of wealth and income as earned and regard the differential earnings of effort, skill, foresight, and enterprise as deserved. Even the prizes of sheer luck cause very little resentment"(*Tobin*, 1970). This statement would probably not be completely true in some, for example, European and Latin American countries.

judgments, and hence cannot be performed using any objective rule. Any unfairness analysis that goes beyond outcomes must face this subjectivity. It is the user of that analysis who should provide the criterion to split the explanatory variables. This is not a simple task. However, it seems that people do have opinions about what they consider acceptable or not, although perhaps they are not ready to offer a strong and coherent philosophical framework to back those opinions.

Suppose the set of explanatory factors of a stochastic outcome x is already divided into a vector of acceptable factors (labeled as A) and a vector of unacceptable ones (labeled as U). The following definition states the concept of unfairness used in this paper.

Definition: *The distribution of a stochastic outcome x is considered to be unfair if and only if there exists a vector A and two different vectors* U_i, U_j *s.t* $E(x/A,U_i) \neq E(x/A,U_j)$

where $E(x/A,U)$ is the expectation of x conditional on vectors A and U. The definition implies that for a situation not to be regarded as unfair, for every given vector A, the expected value of the outcome should be the same regardless of the value of vector U.[9] Notice that for a given A, differences in outcomes are not considered unfair if their conditional expectations are the same. Hence, the definition implicitly assumes that the "basic and unpredictable element of randomness in human responses"[10] that remains after including all explanatory variables into the analysis is regarded as an acceptable source of differences in outcomes.[11]

The main interest of this paper is to measure the *degree* of unfairness and not just the presence of it.[12] In a typical income inequality analysis various indices can be applied to measure dispersion in the income distribution (Gini, Theil, Atkinson, etc.). The same measures can be applied in an unfairness analysis, taking the conditional expectations $E(x/A,U_i)$ rather than the outcomes x as arguments of the measures.

There are at least three reasons why the task of measuring unfairness becomes much harder than measuring outcome inequality. First, we have to find the factors that determine

[9] Notice that this is a weak condition since (i) it does not require equal expected outcomes for different values of each unacceptable variable, but for different values of the whole vector U; (ii) it does not compare two outcomes with different values of A despite the fact that the difference between those two outcomes might be mainly driven by differences in vector U; and (iii) it does not consider fairness *across* acceptable variables (e.g. if ability is considered an acceptable source of differences in education consumption, people might not only require equality of education within each ability group, but also that the expected education consumption for talented youngsters be not lower than for non-talented ones).

[10] *Johnston* (1984).

[11] If, for instance, people decide the value of x by rolling a dice, it is relatively non-controversial to consider the random component as acceptable. But even situations where people are forced to accept the allocation of x generated by *chance* are also likely to be considered fair by many people. One example is the draft for the military service. Differences in outcomes are large (especially in war times). Yet, outcome differences are not seen as unfair if they are entirely due to *chance*.

[12] Notice that according to the definition given above most real-world situations in services like education and health would be considered unfair.

an outcome. Second, we need to split the set of explanatory variables into acceptable and unacceptable sources of differences in outcomes. Finally, while in an outcome inequality analysis the target variable is usually observable, in an unfairness analysis the conditional expected value of an outcome needs to be estimated. Parametric and non-parametric techniques can be applied to obtain those conditional expectations. Non-parametric estimation is especially appropriate for this kind of analysis since capturing the shape of the conditional expectation curve is of special relevance. Despite this advantage, those techniques might not be feasible if the number of variables in the sets A and U is large. Hence, the use of non-parametric techniques leads us to a trade-off between more flexibility and possible mispecification, if we are forced to ignore some potential explanatory variables.

If we consider only the set of observations that share a given value of the acceptable vector A, we can write $x_i=E(x/U_i)+e_i$. The nature of the error term e_i is of great relevance. If e_i is believed to capture only the acceptable intrinsic uncorrelated randomness of the stochastic variable, the error term should not be included in the measure of unfairness. In practice e_i may include variables we are unable to measure or detect as relevant explanatory factors. If those variables are considered acceptable and are uncorrelated with variables in U, taking the conditional expectation of x will not only eliminate the intrinsic stochastic error, but also the variations in x caused by the unobservable acceptable variables. This is a desirable result since differences in outcomes due to acceptable factors should not be computed as unfair. If instead some of the unobservable acceptable variables are correlated with variables in U, taking the conditional expectation of x will not be enough to entirely wash out the effect of those variables on x.[13] An example devoted to illustrate the kind of distortion in unfairness measures generated by the existence of unobservable acceptable explanatory variables is presented in the appendix. Not surprisingly, it is shown that the bias essentially depends on the correlation between unobservable and observable explanatory factors. In addition, and since we are mainly interested in the *comparison* of unfairness measures between variables, the key element in that bias turns out to be the difference between those variables in the degree of correlation between their unobservable and observable explanatory factors.

Consider that e_i is just acceptable uncorrelated randomness. The typical way to tell $E(x/U_i)$ and e_i apart from each observation x_i is to express the conditional expectation as a function of U_i and to assume some structure for that function. But that structure, which is crucial to determine the division between $E(x/U_i)$ and e_i, is essentially arbitrary. To illustrate this point, suppose that non-parametric estimation is chosen. To apply this method first we have to solve the *smoothing parameter selection problem* (see *Härdle* (1990)). In this context, that problem has both a statistical and a conceptual dimension. On the one hand, the choice of a bandwidth (or any other smoothing parameter) is a sample size issue:

[13] The fact that a given explanatory variable is correlated with an unacceptable one may induce some people to consider it unacceptable as well, in which case it should be included into set U.

as the number of observations tends to infinity, the bandwidth should tend to zero. Howevei, given a small sample size, the choice of the bandwidth becomes also a conceptual issue. The selection of the bandwidth implicitly determines the partition between expected value and error. If conceptual considerations and/or additional information lead us to believe that differences in outcomes x are mostly attributable to differences in $E(x/U_i)$, we would choose a small bandwidth that does not smooth the data very much. On the other hand, if the acceptable error term is thought to be responsible for most of the differences across individuals in the data, a larger bandwidth should be selected to be sure to eliminate the stochastic component. The same kind of considerations determines the choice between non-parametric and parametric estimation and the selection among different parametric specifications. In this paper several bandwidths are used to smooth the data.[14] Linear logit regressions, which can be thought of as an extreme way of smoothing the data, are also used to obtain the expected values.

3. *An application: education and health in Argentina*

The approach outlined in last section is applied to the education and health sectors in the Greater Buenos Aires area (GBA).[15] Results for the secondary level of education are also obtained for a sample of other Argentine cities. The information is taken from the Encuesta Permanente de Hogares (EPH), a household survey whose main objective is to gather information about labor market variables. The typical survey, which covers around 4,500 households (more than 11,000 people) in GBA, allows us to know whether an individual is attending school or not. Since no other dimension of the education decision is observable, the consumption of education is treated as a binary variable. The survey also includes some demographic and socioeconomic variables that are used as explanatory factors. The typical EPH does not have questions about health service consumption. However, the May 1992 survey included a special questionnaire that allows us to know whether an individual had consumed various health services or not in the month previous to the survey.

Given the available information, the arguments of the unfairness measures will be the conditional probabilities of attending a given educational level or consuming a given health service. These probabilities are estimated using conventional non-parametric and parametric techniques. All the non-parametric estimations are locally weighted regressions (*lowess*). The smoothed value of the dependent variable x_i is obtained by running a regression of x on the vector of unacceptable variables U using only the observation i and some observations close to i. The number of observations used in a regression is determined by the bandwidth.[16] The regression is weighted using a tricube function that assigns the highest weight to i. The estimated regression is used to predict the smoothed value for x_i.

[14] Given that qualitative results do not substantially change, only those obtained with a bandwidth of .8 are shown (see below).

[15] GBA has around 12 million inhabitants (1/3 of Argentina's total population). It is an exclusively urban area.

[16] A bandwidth of b means that $b.N$ observations are used to smooth each point in the data. The exceptions are the end points, where smaller subsets are used.

The procedure is repeated for each observation. The resulting curve of smoothed values is adjusted so that the mean coincides with the mean of the unsmoothed values. The smoothed value for x_i is interpreted as the estimated probability of consuming x for individual i and is used to compute the unfairness indices. The same procedure is applied using different bandwidths to check for robustness in the order of the indices. The parametric estimations are standard logit regressions. The predicted values of these regressions are used as inputs of the unfairness measures.

The decisions to attend school and to see a doctor presumably depend on many factors. Unfortunately, given the relative small number of observations available, the analysis should keep the dimensionality low and ignore many of those factors. Also, from a practical point of view it is likely that the decision-maker's fairness concerns be posed in low dimensional terms (*e.g.*, being worried about the relation between consumption of a basic service and income). Four explanatory variables are used in this analysis: age, sex, income and family education. Income refers to household income adjusted by demographics. Household income is divided by the number of equivalent adults in the family raised to the power of .8 to capture some degree of household consumption economies of scale.[17] When analyzing education choices for children and youngsters, their earnings are subtracted from family income to get *parental income*. Individuals are divided into two groups according to their family education: those who live in a family where none of the household heads has a high school degree (low-education group L) and the rest (high-education group H). In the following analysis, age is considered an acceptable source of differences in education and health consumption decisions. Income, instead, is considered unacceptable. Gender is unacceptable for education and acceptable for health, since in the latter case it is believed that it basically captures differences in needs. The household education variable might be considered unacceptable in some cases, and acceptable in others, depending on the interpretation of what it is proxy for, and on value judgments.[18] Both cases are treated in this paper.

3.1. Education

The first part of this section is devoted to measure variations in unfairness in secondary school attendance from 1988 to 1997 in GBA. Then, the analysis is extended to other Argentine cities and to the college attendance decision.[19] Table 1 shows attendance rates for

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[17] The equivalence scale was taken from the agency that calculates official poverty statistics, while .8 is taken arbitrarily from a sample of parameters estimated in other studies.

[18] For instance, differences in family education might be thought of as been caused by differences in wealth, and therefore considered unacceptable. If the user of the unfairness analysis is paternalistic, differences in family education might be considered unacceptable, even if those differences are driven mainly by preferences. On the other hand, family education will be regarded as an acceptable variable if preferences are fully respected.

[19] Unfairness in school attendance at the primary level does not seem to be an important problem: attendance rates were always higher than 98% in the last decade.

youngsters in high school age (between 13 and 17) who finished primary school.[20] Attendance rates drop from 1988 to 1992 and have been growing since then. The large increase in 1997 is in part due to the extension of compulsory schooling to the first year of secondary school.[21] However, even for youngsters in the 15-17 age range, for whom high school was not compulsory, attendance rates sharply rose in 1997. Naturally, the group of youngsters from families with low education has lower attendance rates. Males have slightly lower attendance rates than women.

Table 1
Attendance rates
Secondary school
Greater Buenos Aires, 1988-1997

	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997
All	74.5	73.8	72.8	72.0	72.0	72.8	73.2	74.0	75.7	79.9
Group L	64.8	64.0	64.0	64.1	61.9	62.5	60.8	62.8	66.2	72.4
Group H	96.0	92.9	92.7	90.8	92.6	92.9	93.8	92.5	91.4	94.2
Males	72.4	71.8	71.3	68.9	68.9	69.8	69.2	73.2	75.5	78.0
Age 13-14	86.1	85.8	82.7	85.2	83.1	87.2	83.9	85.9	86.6	93.2
Age 15-17	67.3	67.5	66.0	63.6	65.3	63.9	67.5	67.5	69.3	73.0

Source: EPH GBA, May. *All* refers to all youngsters between 13 and 17 who finished primary school. Group L comprises those youngsters from families where none of the household heads has a high school degree. The rest of the youngsters are in group H.

Due to the relative small number of observations, the non-parametric analysis is limited to two explanatory variables: log parental income adjusted by demographics and parental (or family) education. If parental education is considered an unacceptable factor, all youngsters are considered together into a single unfairness index (I). On the other hand if parental education is considered an acceptable factor, two indices should be calculated, one for each parental education group (I_l and I_h). The arguments of these unfairness measures should be the probabilities of high school attendance conditional on parental income for all youngsters who qualify to attend high school and who belong to a given parental education group. The conditional probabilities are estimated using *lowess*. Results for two selected years, 1994 and 1997, using a bandwidth of .8 are shown in figures 1 and 2. Observations marked with a circle (plus sign) are the estimated probabilities of youngsters from more-educated (less-educated) families. Only the estimated values marked with a circle are used to obtain I_h, plus signs are used to get I_l and both circles and plus signs are used to calculate I. From figures 1 and 2 it is clear that parental income affects the schooling attendance decision, even when controlling for parental education. That effect is more dramatic in group L. From the inspection of both figures unfairness in high school attendance seems to be lower in 1997: the curve of predicted probabilities for group L seems flatter, and in addition the

[20] The May surveys usually capture more than 800 youngsters in that condition.
[21] Actually, the whole educational system was changed. Primary school (now called "EGB") was extended from 7 to 9 compulsory years.

distance between curves L and H seems smaller. Of course, these presumptions should be given precise meaning: that is the purpose of the unfairness indices.

Figure 1
Probability of attending high school
Lowess estimates
May, 1994

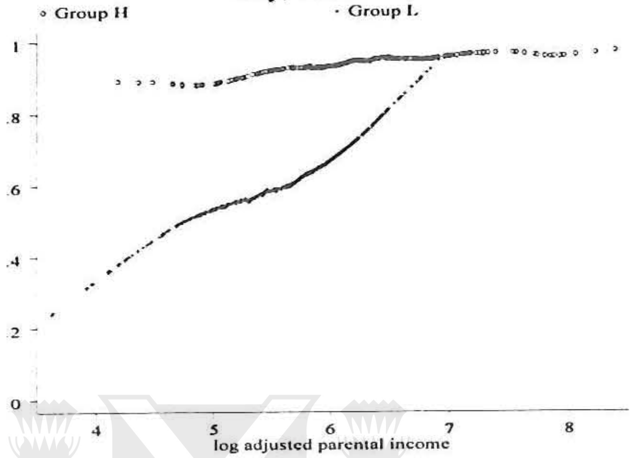
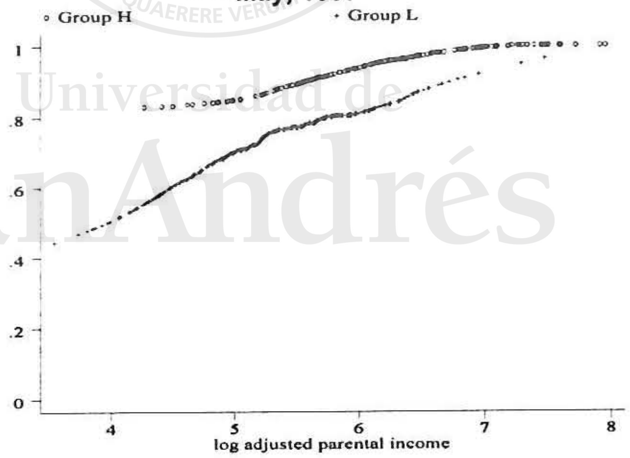


Figure 2
Probability of attending high school
Lowess estimates
May, 1997



Parametric estimation allows for a richer specification. A logit regression of the attendance decision is run on parental income, a gender dummy and age. A separate regression is run for each family education group. Table 2 shows the results for 1994 and 1997. Notice that age is likely to be considered an acceptable source of differences in attendance. In that case a separate regression should be run for individuals of the same age and parental education. However, given the number of observations available, I prefer not to divide the sample in age groups and instead calculate the expected probabilities fixing the age at some value.

Table 2
Logit regressions of the high school attendance decision
Greater Buenos Aires, May 1994 and 1997

	Group L				Group H			
	1994		1997		1994		1997	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Log adjusted parental income	0.74	0.16	0.97	0.16	0.56	0.34	1.30	0.41
Female	0.39	0.18	0.13	0.22	0.50	0.47	0.75	0.62
Age	-0.35	0.07	-0.66	0.09	-0.58	0.19	-0.76	0.27
Constant	1.47	1.32	6.05	1.45	7.99	3.61	6.80	4.47
Observations	560		527		340		277	
chi2(6)	55.5		94.4		14.0		22.1	

Figure 3 shows the predicted values from each regression setting age equal to 15. Again, circles are used to obtain I_h, plus signs are used to get I_l and both circles and plus signs are the inputs for I. From the figures predicted probabilities seem to be more concentrated around its mean in 1997, implying lower unfairness.

Figure 3
Probability of attending high school
Logit estimates
May, 1994

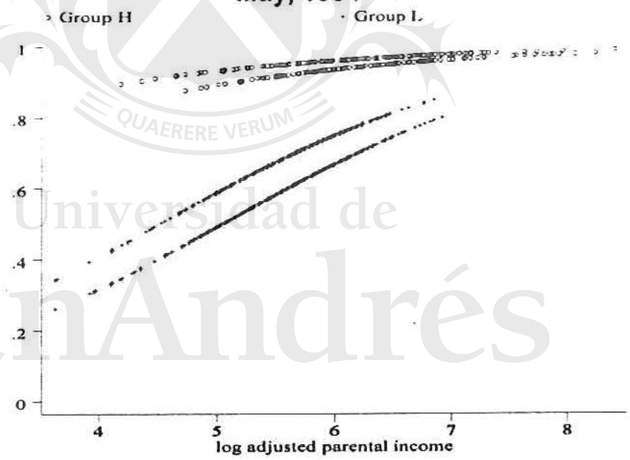


Figure 4
Probability of attending high school
Logit estimates
May, 1997

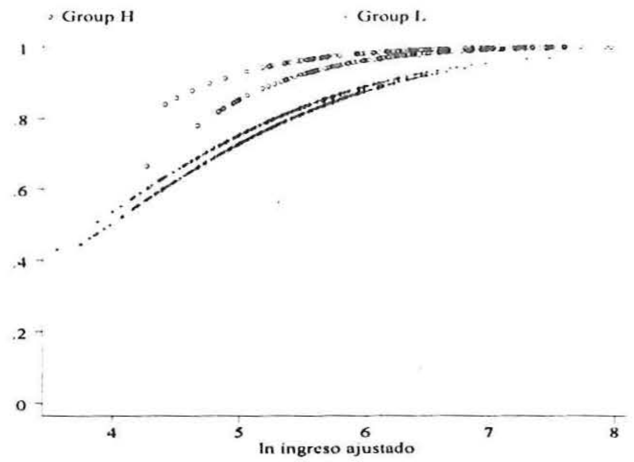


Table 3 shows unfairness indices for secondary school attendance. The first panel presents measures which take parental education as an unacceptable source of differences in high school attendance. The next two panels show the results when analyzing separately the parental education groups. Several typical inequality indices are calculated from the individual conditional probabilities estimated by both lowess and logit regressions. The table shows two of the most widely used measures: the Gini coefficient and the Atkinson index with two alternative inequality aversion coefficients.[22] Figure 5 illustrates the results for the Gini coefficient. The first panel of table 3 and the top two lines of figure 5 show the results when parental education is considered unacceptable. Unfairness in secondary school attendance grew until 1992 or 1994 (depending on the estimation procedure used) and has been falling since then. The drop in unfairness measures is most dramatic in 1997 reaching the lowest value of the decade. This result is robust to all indices and estimation procedures applied. Unfairness seems to be closely related to attendance rates. Given that most of the youngsters from rich and well-educated families do attend high school, an increase in attendance rates basically means that a higher proportion of socially disadvantaged youth make it to high school, thus lowering unfairness. Unfairness is much higher in group L than in H. For the former group the Gini increased until 1991, decreased until 1993, grew again until 1995 and then drop in 1996, and especially in 1997 when high school attendance rate jumped from 66% to 72%. There is not a clear pattern in the Gini for youth in group H. In any case, the values are very low.

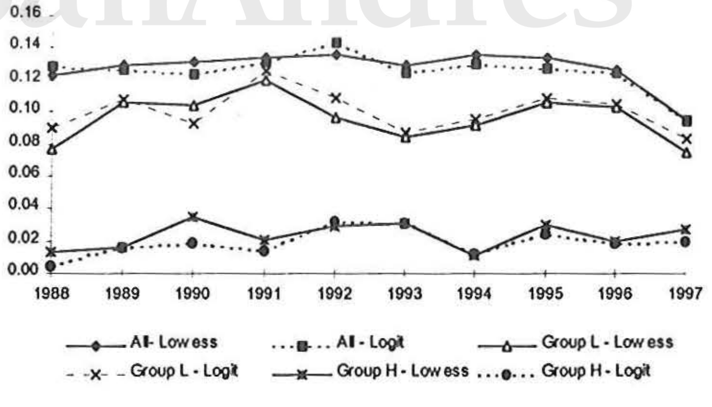
[22] These measures share the property of scale invariance, which, although widely accepted, implies a value judgment that might not be shared by all people in all situations.

Table 3
Unfairness indices
High school attendance
Greater Buenos Aires 1988-1997

	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997
All youngsters										
Lowess										
Gini	0.123	0.129	0.131	0.133	0.136	0.129	0.136	0.134	0.127	0.094
Atkinson (α=-.5)	0.349	0.434	0.418	0.459	0.428	0.389	0.457	0.444	0.420	0.233
Atkinson (α=-1)	0.461	0.589	0.561	0.621	0.566	0.518	0.609	0.596	0.571	0.317
Logit										
Gini	0.128	0.127	0.124	0.131	0.143	0.125	0.130	0.127	0.125	0.094
Atkinson (α=-.5)	0.482	0.484	0.423	0.462	0.651	0.398	0.424	0.467	0.454	0.296
Atkinson (α=-1)	0.667	0.673	0.580	0.633	0.918	0.539	0.571	0.645	0.628	0.413
Group L										
Lowess										
Gini	0.077	0.106	0.103	0.119	0.096	0.084	0.091	0.106	0.103	0.075
Atkinson (α=-.5)	0.135	0.310	0.278	0.349	0.218	0.173	0.209	0.266	0.285	0.173
Atkinson (α=-1)	0.178	0.424	0.378	0.469	0.286	0.231	0.280	0.355	0.389	0.238
Logit										
Gini	0.089	0.107	0.092	0.126	0.109	0.087	0.096	0.108	0.104	0.083
Atkinson (α=-.5)	0.207	0.346	0.238	0.407	0.314	0.231	0.245	0.358	0.317	0.225
Atkinson (α=-1)	0.281	0.480	0.326	0.554	0.429	0.320	0.335	0.496	0.438	0.313
Group H										
Lowess										
Gini	0.013	0.016	0.034	0.021	0.029	0.031	0.012	0.030	0.020	0.027
Atkinson (α=-.5)	0.010	0.007	0.044	0.010	0.020	0.022	0.004	0.024	0.009	0.018
Atkinson (α=-1)	0.014	0.010	0.060	0.014	0.027	0.030	0.005	0.032	0.012	0.024
Logit										
Gini	0.004	0.016	0.019	0.014	0.032	0.031	0.012	0.025	0.019	0.020
Atkinson (α=-.5)	0.001	0.006	0.009	0.005	0.038	0.035	0.004	0.020	0.009	0.014
Atkinson (α=-1)	0.001	0.008	0.012	0.006	0.051	0.047	0.005	0.027	0.012	0.019

Note: Atkinson indices are calculated from a CES function with inequality aversion coefficient equal to (1-α). Values are multiplied by 10.

Figure 5
Gini coefficient
High school attendance
Greater Buenos Aires 1988-1997



Comparison across cities

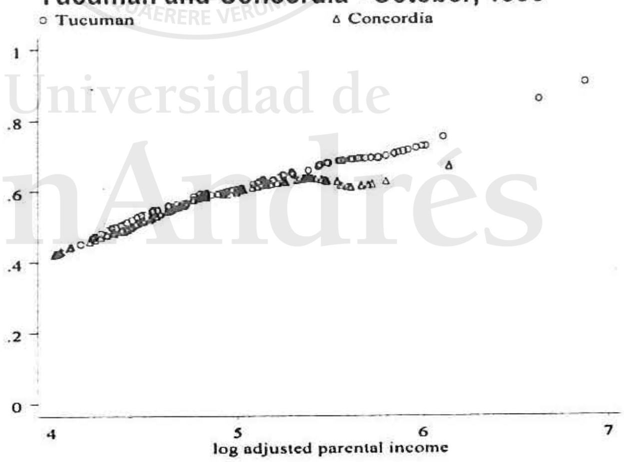
Table 4 shows high school attendance rates and Gini unfairness indices calculated from the October 1996 EPH taken in several Argentine cities. Since most group H youngsters attend high school, unfairness is essentially determined by the degree in which parental income (and gender to some extent) affects the attendance decision in group L youngsters.

Table 4
Attendance rates and the Gini coefficient
High school
Argentine cities, October 1996

	Attendance rates			All		Group L		Group H	
	All	Group L	Group H	Lowess	Logit	Lowess	Logit	Lowess	Logit
Concordia	63.9	54.7	92.4	0.146	0.133	0.075	0.089	0.025	0.028
Gran Buenos Aires	73.6	62.7	94.0	0.133	0.126	0.101	0.107	0.015	0.016
La Plata	80.6	71.0	96.3	0.101	0.103	0.074	0.063	0.019	0.016
Mar del Plata	81.5	71.0	96.0	0.105	0.087	0.102	0.077	0.018	0.016
Mendoza	73.1	60.2	93.9	0.140	0.110	0.069	0.057	0.052	0.032
Neuquén	78.3	65.5	96.2	0.130	0.108	0.092	0.062	0.025	0.028
Río Gallegos	92.4	88.0	97.9	0.037	0.022	0.024	0.010	0.014	0.008
Rosario	76.7	66.3	95.2	0.109	0.087	0.055	0.046	0.023	0.016
Santa Fé	84.9	78.1	95.9	0.081	0.068	0.081	0.079	0.028	0.023
Tucumán	68.0	56.5	89.9	0.161	0.163	0.131	0.143	0.034	0.017

Unfairness indices are again related to attendance rates. However, there are some exceptions. Tucumán has a higher attendance rate than Concordia but also a higher Gini coefficient. Figure 6 illustrates the case of these cities.

Figure 6
Probability of attending high school
Group L youngsters
Lowess estimates
Tucumán and Concordia - October, 1996



Probabilities for youngsters with log adjusted parental income below 5.2 are similar in both cities. In contrast, estimated probabilities for richer youngsters are higher in Tucumán. This explains both the higher attendance rate and the higher Gini index in that city. The example is useful to illustrate a familiar point in the inequality literature, which is also present here: unfairness measures should not be used alone in assessing a welfare comparison. The higher unfairness measure in Tucumán is not necessarily a sign of a socially worse situation than in

Concordia. In fact, if the welfare function were increasing in the probability of high school attendance, the situation in Tucumán, although more unequal would be socially better than in Concordia.

College

The tertiary level of education in Argentina comprises universities and technical colleges. Most students are in the 18-23 range of age. Universities in Argentina are mostly attended by the wealthy. However this may be just the consequence of inequities in previous educational levels. To single out unfairness in college attendance the sample is restricted to those individuals between 18 and 23 years old who finished high school. Youngsters who are family heads are ignored since we do not observe their parental education from the survey. Table 5 shows that attendance rates drop from 1988 to 1993, increased until 1996 and drop in 1997. Attendance rates are higher for the group of youngsters with at least a family head with a high school degree. Attendance rates for males are in general slightly lower than for females.

Table 5
College attendance rates
Greater Buenos Aires

	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997
All	61.0	54.8	55.0	53.9	54.1	49.6	56.7	58.2	61.3	60.8
Group L	54.1	45.3	40.5	39.8	39.4	34.0	45.7	45.5	48.6	44.8
Group H	67.4	62.5	66.2	66.7	67.7	60.8	64.5	66.3	69.2	70.3
Males	68.6	51.2	56.1	49.0	55.0	43.8	51.1	56.0	57.0	58.0

Source: EPH GBA, May. *All* refers to all youngsters between 18 and 23 who finished high school. Group L comprises those youngsters from families where none of the household heads has a high school degree. The rest of the youngsters are in group H. Youngsters who are not family heads are ignored.

Unfairness indices calculated using parametric and non-parametric techniques are shown in table 6 and figure 7.[23] If parental education is considered unacceptable, various measures indicate that unfairness in college attendance increased until 1991, drop until 1994, and then increased again. Notice that the latter increase has occurred even when college attendance rates grew in that period. Unfairness for group L increased until 1993 and has been high since then.[24] Finally, unfairness in group H steadily grew from 1992/3 to 1996.

[23] In the logit regressions when calculating the estimated conditional probabilities, age is set at 20.

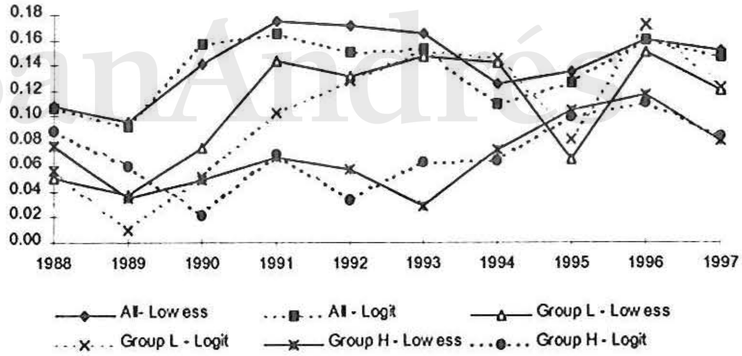
[24] Measures are atypically low in 1995.

Table 6
Unfairness indices
College attendance
Greater Buenos Aires 1988-1997

	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997
All youngsters										
Lowess										
Gini	0.107	0.095	0.141	0.175	0.171	0.166	0.126	0.135	0.161	0.152
Atkinson (α=-.5)	0.027	0.022	0.052	0.085	0.077	0.101	0.051	0.041	0.071	0.059
Atkinson (α=-1)	0.036	0.029	0.070	0.117	0.103	0.142	0.071	0.053	0.097	0.080
Logit										
Gini	0.107	0.092	0.157	0.165	0.151	0.153	0.110	0.126	0.161	0.147
Atkinson (α=-.5)	0.029	0.019	0.063	0.067	0.059	0.057	0.029	0.041	0.073	0.058
Atkinson (α=-1)	0.040	0.026	0.084	0.090	0.080	0.077	0.040	0.056	0.100	0.080
Group L										
Lowess										
Gini	0.050	0.038	0.075	0.144	0.131	0.148	0.143	0.067	0.151	0.121
Atkinson (α=-.5)	0.008	0.006	0.028	0.051	0.038	0.052	0.080	0.011	0.066	0.053
Atkinson (α=-1)	0.011	0.008	0.039	0.068	0.050	0.068	0.116	0.015	0.091	0.074
Logit										
Gini	0.057	0.009	0.052	0.102	0.128	0.152	0.146	0.082	0.172	0.123
Atkinson (α=-.5)	0.007	0.000	0.007	0.029	0.039	0.052	0.058	0.018	0.095	0.039
Atkinson (α=-1)	0.010	0.000	0.009	0.040	0.052	0.068	0.079	0.024	0.134	0.053
Group H										
Lowess										
Gini	0.077	0.035	0.050	0.067	0.058	0.029	0.073	0.105	0.117	0.080
Atkinson (α=-.5)	0.015	0.003	0.006	0.013	0.008	0.002	0.013	0.025	0.043	0.015
Atkinson (α=-1)	0.021	0.004	0.008	0.016	0.011	0.003	0.017	0.033	0.059	0.020
Logit										
Gini	0.088	0.061	0.022	0.070	0.034	0.064	0.065	0.100	0.112	0.085
Atkinson (α=-.5)	0.020	0.009	0.001	0.012	0.003	0.010	0.010	0.029	0.033	0.019
Atkinson (α=-1)	0.027	0.012	0.002	0.016	0.004	0.013	0.013	0.040	0.045	0.025

Note: Atkinson indices are calculated from a CES function with inequality aversion coefficient equal to (1-α). Values are multiplied by 10.

Figure 7
Gini coefficient
College attendance
Greater Buenos Aires 1988-1997



Before turning to the health sector, a word on the absence of ability in the analysis is worth mentioning. If ability is acceptable and is thought to be correlated with some other explanatory variables (*e.g.* parental income), estimates are surely biased. However, according to the discussion at the end of last section, if the correlation between ability and other variables has not changed much in the last decade then qualitative results are reasonably robust.[25]

3.2. Health

In May 1992 a special questionnaire including questions on health insurance coverage and health services consumption was included in the EPH. Only the case of visits to a doctor is treated in detail here. Some results for health insurance and the rest of the services are briefly summarized in the last part of this section. Unfortunately, the available data covers only one year (1992) and one region (GBA). Therefore, the scope for comparisons is very limited. The main goal of this section is to investigate differences in unfairness in visits to doctors across age groups. Presumably, governments are interested in detecting in which group unfairness is a more severe problem. Since health policy can be targeted to a specific age group, the information could be useful in guiding policy.

The May 1992 EPH asks each person whether she was seen by a doctor during the month previous to the survey. Table 7 presents the basic information classified into four age groups. 22% of the children in the survey were seen by a doctor during April 1992. That percentage is similar for young adults, lower for youngsters (17%) and higher for adults over 50 (37%). The proportion of children and youngsters who are seen by a doctor in a month is significantly larger in high-education households compared to low-education ones. That pattern is weaker for adults.

Table 7
Proportion of individuals who visited a doctor in a month
Greater Buenos Aires, May 1992

	0-12	*13-29*	*30-49*	*50-*
All	22.1	17.0	21.7	36.7
Group L	20.1	14.8	20.7	36.1
Group H	25.7	21.2	23.1	38.2

Source: EPH GBA, May 1992. *All* refers to all individuals in the survey. Group L comprises those individuals from families where none of the household heads has a high school degree. The rest of the individuals are in group H.

Age, gender, log adjusted family income, and family education are considered explanatory factors of the decision to see a physician.[26] Within each age group a separate lowess regression using log adjusted family income as the only explanatory variable was run for each family education group. Several bandwidths were used to smooth the data. Since results do not change for reasonable degrees of smoothing, only those obtained with a

[25] If the positive correlation between ability and parental income increased from one year to another then we would expect measures that do not consider ability to capture an spurious increase in unfairness.

[26] An important unobservable explanatory variable is the need for the service. Needs are considered to be acceptable variables. Therefore, the unfairness analysis should be ideally performed dividing the population into people who need a health service, and people who do not. The division of the survey into age groups controls for some of the differences in needs, but clearly not for all. Thus, the possibility of a bias arising from the unobservability of needs should be kept in mind.

bandwidth of .8 are reported.[27] The logit regressions include income, gender and age as explanatory variables. Since gender and age are considered acceptable sources of differences in the decision to see a physician, the predicted probabilities are calculated with both variables fixed at a given value.[28] Table 8 displays different unfairness indices calculated from the smoothed data.

Table 8
Unfairness indices
Visits to a doctor
Greater Buenos Aires, May 1992

	0-12	*13-29*	*30-49*	*50-*
All				
Lowess				
Gini	0.128	0.122	0.064	0.043
Atkinson (α=-.5)	0.444	0.338	0.110	0.048
Atkinson (α=-1)	0.607	0.446	0.143	0.065
Logit				
Gini	0.117	0.114	0.070	0.023
Atkinson (α=-.5)	0.316	0.309	0.114	0.014
Atkinson (α=-1)	0.418	0.403	0.151	0.019
Group L				
Lowess				
Gini	0.139	0.077	0.029	0.032
Atkinson (α=-.5)	0.488	0.136	0.021	0.025
Atkinson (α=-1)	0.661	0.179	0.028	0.034
Logit				
Gini	0.151	0.080	0.015	0.005
Atkinson (α=-.5)	0.548	0.152	0.006	0.001
Atkinson (α=-1)	0.733	0.202	0.007	0.001
Group H				
Lowess				
Gini	0.067	0.046	0.088	0.049
Atkinson (α=-.5)	0.109	0.072	0.177	0.102
Atkinson (α=-1)	0.142	0.096	0.232	0.142
Logit				
Gini	0.012	0.015	0.097	0.026
Atkinson (α=-.5)	0.003	0.006	0.220	0.016
Atkinson (α=-1)	0.005	0.007	0.292	0.021

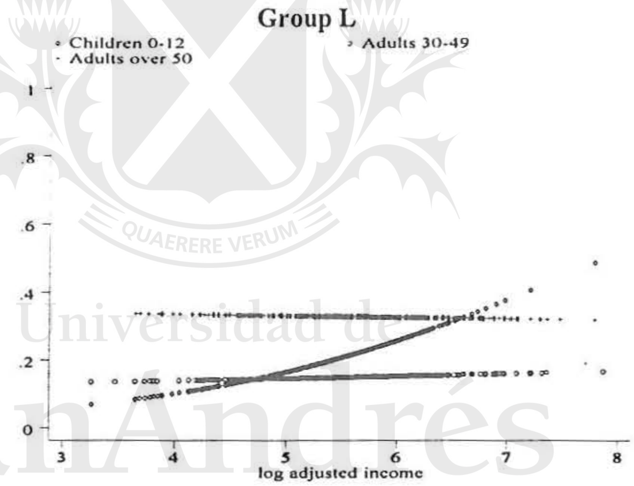
Note: Atkinson indices are calculated from a CES function with inequality aversion coefficient equal to (1-α). Values are multiplied by 10.

When considering family education as unacceptable, unfairness in visits to a physician is decreasing in age, regardless of the measure and the smoothing procedure used. Children have the highest indices. They are followed by youngsters, young adults and adults over 50. The last two panels of table 8 suggest that the differences between children and older people observed in the first panel are basically due to high unfairness in children from low-

[27] See *Gasparini* (1997) for an analysis with several bandwidths.
[28] Predicted probabilities are computed for males and for the following ages: 5, 21, 40 and 65.

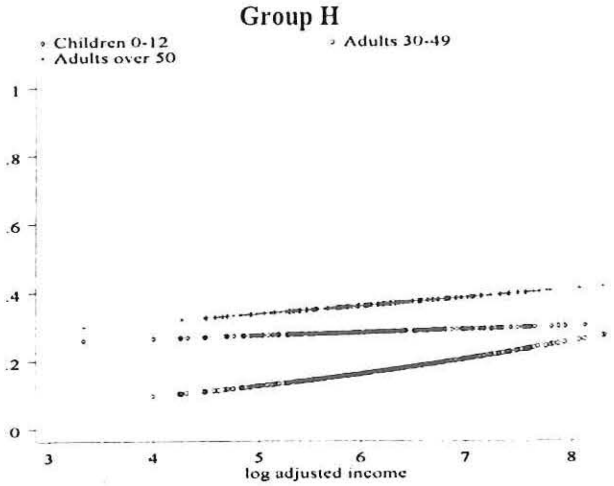
education households. When considering households in group L the indices for children are always significantly larger than those for the other groups. Such a result is robust to all unfairness measures and smoothing procedures applied. That is not the case for individuals in group H. Figure 8 illustrates the results by showing the predicted probabilities for children and adults calculated from logit regressions. While the probability of being seen by a doctor clearly increases with income for group L children, that is not the case for adults in the same family education group.[29] In contrast, for group H individuals the children's curve is the flattest of the three. Figure 8 also suggests that while income does not seem to significantly affect the decision to see a doctor for adults from less-educated households, it does affect that decision for adults in the more-educated group.[30] In fact, for group H unfairness indices for adults under 50 have the highest values of all age groups.

Figure 8
Probability of visiting a doctor
Children and adults
Logit estimates



[29] In fact the estimated probabilities for adults over 50 are slightly falling with income.

[30] The steep curves for group L children and group H adults under 50 shown in figure 8 could be two linked phenomena. A plausible, but only conjectural explanation could be the following. Suppose well-educated adults are more aware of the importance of good health care for the future development of their children than low-educated adults are. Poor well-educated parents would make every possible effort to guarantee an appropriate health care for their children. That effort may include a reduction in their own health expenses (that effect could operate through both the budget and the time constraint). If that substitution in health care between children and parents in poor well-educated households takes place, the differences in health consumption would be reduced for children and enlarged for adults (compared to the situation in low-education households, where such a substitution does not take place).



Two qualifications are important to stress at this point. The first one refers to the correlation between needs and income. It is conceivable that these two variables be negatively correlated.[31] If that were the case, unfairness would be a more serious problem than what table 8 indicates. Also, a negative correlation might alter the assessment of comparisons among age groups. But notice that for the conclusion that unfairness is a more serious problem for children than for grown-ups to be contradicted, the correlation between needs and income should be much more important for the latter group than for the former, which in principle is not an obvious fact. The second qualification refers to the fact that a higher variability in the children's data does not automatically mean a more serious social problem. For instance, the lowest estimated probability of visiting a doctor for 5 years-old children is around .075, depending on the smoothing procedure applied. Suppose health authorities consider that a probability of visiting a doctor in a given month equal to .075 is enough to keep 5 years-old children healthy, and that higher probabilities do not significantly alter their health status. Hence, the fact that some parents take their children more often to the doctor than others would be regarded as irrelevant to the children's health, which is the variable social planners are interested in. In that case, the high unfairness indices for children would not be of any social concern.[32]

Other results

Gasparini (1997) finds that high unfairness for children is not restricted to doctor visits. The group of children presents higher indices than adults over 65 in all services considered: treatments, x-rays and lab tests. Also, the situation regarding health insurance seems to be

[31] However, reported need is usually positively correlated with income. Cultural and educational factors may affect the assessment of whether a health service is needed or not.

[32] Casual investigation indicates that a probability of .075, which approximately means on average a visit to a physician every 13 months, is too low.

more unfair for children than people in their sixties and seventies.[33] *Gasparini* (1997) also finds that the public-private choice of the medical institution is greatly affected by family income. If there is a concern about equity in the opportunity to receive health care of the same quality, and public hospitals are proved to be of a lower quality than private clinics (a plausible conclusion in the Argentine case), then differences in the probability of consuming a health service in a private clinic among individuals may represent an unfair situation. Again, the group of children presents the highest indices, followed by youngsters, adults, and the elderly. Contrary to the decision to see a doctor, the high indices are not restricted to the low-education group. Household income seems to have a big impact on the public-private decision, regardless of the educational level of the household.

4. *Final remarks*

The need for empirical work on the measurement of unfairness in the distribution of some goods and services has been repeatedly stressed. This paper takes a step in that direction by presenting a framework based on the idea that only differences in outcomes caused by differences in some "unacceptable" variables are regarded as unfair. This leads to the necessity to identify the explanatory variables and classify them according to their acceptability as sources of outcome differences. Given the stochastic nature of the social phenomena, it also introduces the need to work with conditional expected values of the outcomes, a fact that generates various estimation problems. Traditional inequality indices can be applied to measure the degree of unfairness by using the estimated conditional expectations as arguments of those indices. The paper illustrates the approach with an application to education and health in the Greater Buenos Aires area some other Argentine cities. The analysis presented is far from being complete. However, I believe it offers some insights on the measurement of unfairness in the distribution of goods and services which, hopefully, could be useful in future research. I also believe the paper is useful for policy-makers in Argentina, since it identifies and documents some potential unfair situations in the education and health sectors that deserve careful analysis.

[33] The existence of an extensive public health insurance system for the elderly probably contributes to the fact that the great majority of them are covered, which in turn explains the very low unfairness indexes. Children are usually included in the coverage of their parents, which is typically provided on the job. However, most of the informal workers, who also tend to be the poorest ones, do not have insurance, and hence, their children are uncovered.

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Appendix

Unobservable variables: an example

Assume there are only two explanatory variables of an outcome x: an acceptable variable a and an unacceptable one u. Suppose that a is unobservable. Hence, $E(x/a,u_i)$ cannot be calculated. We are interested in assessing the departure of the *computed* unfairness, *i.e.* the measure of unfairness obtained by using $E(x/u_i)$, from the *real* unfairness, *i.e.* the measure of unfairness that we would obtain by using $E(x/a,u_i)$ if a were observable. Notice that when a is unobservable, only a single measure of unfairness in the distribution of variable x can be constructed from the expected values $E(x/u)$. On the other hand, when a is observable, a measure of unfairness can be (and should be) computed for each value of a. To make both cases comparable, I construct a weighted average of the latter unfairness measures over all possible values of a. To keep things simple, assume half of the population has characteristic u_i while the other half has characteristic u_j, and restrict the measure of unfairness in x to the ratio of the conditional expected values of x. Hence, the measure of unfairness in the distribution of x when a is observable would be

$$\mu_x \equiv \sum_a \gamma_{ax} \frac{E(x/a,u_i)}{E(x/a,u_j)} \equiv \sum_a K_{ax}$$

where γ_{ax} is the fraction of variable x corresponding to individuals with characteristic a (*i.e.* $\gamma_{ax}=P(a)E(x/a)/E(x)$). When a is unobservable μ_x cannot be computed. Instead, we can measure

$$\lambda_x \equiv \frac{E(x/u_i)}{E(x/u_j)}$$

Suppose we want to compare unfairness for two different variables, x and y. After some algebra,

$$(\mu_x - \mu_y) = (\lambda_x - \lambda_y) + \sum_a (K_{ax}.[1-\varphi_{ax}.\omega_{ax}] - K_{ay}.[1-\varphi_{ay}.\omega_{ay}]) \qquad \text{(A)}$$

where $\varphi_{ax} \equiv \dfrac{P(a/u_i)}{P(a/u_j)}$ computed with the data on x, and $\omega_{ax} \equiv \dfrac{\gamma_{axu}}{\gamma_{ax}}$,

where γ_{axu} is good x consumption by those people with characteristics a and u_j over x consumption by all people with characteristic u_j (i.e. $\gamma_{axu}= P(a/u_j)E(x/a,u_j)/E(x/u_j)$).[34] Equation (A) shows the difference in *real* unfairness between two variables (μ_x-μ_y) as a function of the *computed* difference (λ_x-λ_y). The bias of the estimate depends on the sign and the (relative) values of φ_{ax} and φ_{ay}, which capture the correlation between a and u in the data for each variable. In addition, the bias also depends on the values of K_a and ω_a.

[34] The value ω_{ax} reflects the extent to which differences in the mean value of x associated with a given value of an acceptable variable differ across groups (*e.g.* the extent to which the increase in attendance levels brought about by having a higher native ability differs across income groups).

The following example is constructed to isolate the effect of the correlation terms φ_{ax} and φ_{ay}.

Consider the decision to consume a given health service in two regions, *x* and *y*. We are interested in assessing the difference in unfairness between the two regions. For illustrative purpose, suppose that income is the only unacceptable variable, and that the population in each region is evenly divided into rich people (u_i) and poor people (u_j). Also, assume the need for the service is the only acceptable unobservable variable, which can take two values: *s* if the person is sick and *h* if she is healthy. Presumably, health service consumption by healthy people is zero, so $\gamma_s=1$ and $\gamma_h=0$. After some algebra,

$$\lambda_x - \lambda_y = \mu_x . \varphi_{sx} - \mu_y . \varphi_{sy} \qquad \text{(B)}$$

Take the case where the *computed* unfairness is more severe in region *x*, *i.e.* $\lambda_x>\lambda_y>1$. What can be inferred about *real* unfairness, *i.e.* about the difference between μ_x and μ_y? As equation (B) shows, the answer to that question depends on the correlation between needs and income in the two regions. If that correlation is thought to be negative (*i.e.* $0<\varphi_{sx}<1$, $0<\varphi_{sy}<1$), there are two possible cases.

(i) When $\varphi_{sx}\leq\varphi_{sy}$, if $\lambda_x>\lambda_y$, we can be sure that $\mu_x>\mu_y$. The *computed* unfairness measure will respect the order of the *real* measure.

(ii) When the correlation between needs and income is more severe in region *y*, *i.e.* $\varphi_{sx}>\varphi_{sy}$, if $\lambda_x>\lambda_y$, nothing can be said about the sign of (μ_x-μ_y) unless we have some idea of the relative magnitude of φ_{sx} and φ_{sy}.

The previous analysis highlights the point that in some cases a precise estimate of the correlation between two explanatory variables is not necessary in order to assess the result of the unfairness comparison between two dependent variables. In our example, if the computed unfairness measure is higher in region *x*, and there is no reason to believe that the negative correlation between needs and income is more severe in region *y*, we may be reasonably confident in regarding the consumption of health services more unfair in region *x* than in region *y*. Notice that to make that statement, knowledge of the precise values of the correlations is not needed.[35]

[35] Although we may be reasonably confident in stating that unfairness is more serious in *x*, we cannot tell whether the situation in *y* is fair or unfair without knowing the exact value of φ_{sy}. Furthermore, notice that I am implicitly assuming that "reverse" unfairness is not possible (*i.e.* a case where, given equal needs, poor people consume more health services than rich people). If that case is allowed, the precise values of both correlations are necessary to assess the results of the comparisons.